Army Research Laboratory

The Human Factors of Sensor Fusion

by Bruce P. Hunn

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14. ABSTRACT

This report discusses select, cognitively based principles associated with the sensor fusion process. A review is made of the standard definitions and descriptions of sensor fusion from an information processing perspective, and that review is tied to basic principles of human cognitive processes which are involved with processing information. Each step of the definition of sensor fusion provided by the Joint Directors of Laboratories is used as a basis of comparison in this report, and elements of human cognition associated with those steps are described in theory and practice. Comparisons of machine cognition are contrasted and compared with human cognition, and recommendations are made about allocation of functions to human and machine in sensor-fused information systems. Implications of sensor fusion as applied to military operations are also discussed.

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1. Introduction

This report discusses how human factors engineering (HFE) is a critical element in the process of sensor fusion. For this report, the definition of sensor fusion is the one created by the Joint Directors of Laboratories (JDL)[1]. With the JDL definition and models, we review each sensor fusion process step from an HFE perspective, we discuss how human factors variables play a significant role for each element of that process, and we discuss how enhancing the role of HFE in the sensor fusion process will result in a more effective human-machine system. Examples to illustrate these issues often refer to the military domain, military aviation, military intelligence, automated systems, or computer operations.

1.1 Background

1.1.1 Basic Concepts

Sensor fusion is the process of collecting data, combining those data through a variety of methods, with a variety of sensing technologies, and presenting those data as an integrated product to a machine or a human. The basic advantage to fusing data is that (a) it should be faster and more effective in presentation than if the data were not fused and (b) combining data results in a richer, more intelligible output that is functionally greater than the sum of its parts. The following definition emphasizes the concept of fusion from a cognitive perspective, regardless of the type of sensor system involved:

> Fusion pools multiple bodies of evidence to produce a single body of evidence that emphasizes points of agreement and de-emphasizes points of disagreement (SRI[2], 2006).

This definition of fusion emphasizes that the process of fusing data is essentially like a logical argument, in which principles, facts, and rules all combine to form and then persuade a conclusion. It is analogous to the testing of a hypothesis in the scientific process and is called an evidential operation (SRI, 2006); however, fusion is also selective in its processing of information and may not always follow a strict *a priori* logical approach. This is evident in the consideration of human-based fusion of information where heuristics (rules of thumb) or recognition-primed decisions may sort information in ways that machines are not currently capable of doing. In principle, fusion may be accomplished by human or machine systems.

Most of the discussion in this report relies on the fact that machines have electro-mechanical sensors and computer-based cognition, whereas humans have the five senses plus human cognition. Humans combine the input of their senses into a cohesive product through cognition, which

[1] Army, Navy, and Air Force science and technology directors
[2] not an acronym

then can result in actions. As a discussion point, it is posited that humans operate in ways similar to machines, from the standpoint of combining input data and information into an output action. This system's view recognizes differences as well as similarities between machines and humans in the acquisition and processing of data, as well as the final output products achieved by both. Some of these similarities and differences are discussed in this report.

Traditional sensor fusion often involved detailed mathematical algorithms that controlled the processing of information to reach a complex goal such as detecting, classifying, and identifying a target (Ceruti, 2004). However, for the purposes of this discussion, the interaction of human cognitive processes in creating and using information is the focus of the discussion. For example, in the aviation environment, some sensors provide system status information, others provide mission information, while still others provide communications linkages, weapons status, or current enemy threat status. A similar process is followed in the electronic warfare environment where "multiple levels of abstraction, multiple sensors and various evidential operations all combine to predict changes in observables" (SRI, 2006). The original goal for electronic warfare and aerospace system's sensor fusion was to combine all these sources of data into a cohesive whole from which a machine or human operator could draw in order to make more effective operational decisions (Bowman & Murphy, 1980). This approach for aerospace was in marked contrast to earlier aerospace systems where routines were fully automated (programmed or "hard wired" as in an early ballistic missile), and it was also in contrast to systems where federated or isolated sensors, acting as single sources and providing information for a single purpose, were usually monitored by a human operator (as in an early aircraft cockpit or an intelligence analyst monitoring one radio channel). Now, on advanced aircraft such as the F-22, the pilot manipulates the throttles to provide a *thrust request* from the central processing computer on the aircraft, and the computer in turn determines if that request can be complied with, based on fused input from sensors that monitor aircraft and external parameters. Those variables are in turn fused by a main-frame computer and the thrust request is completed or mitigated, which is very different from traditional manual control of that process. Likewise, modern electronic warfare systems may include sensor feeds from multiple sources that are combined on a single display format into a new image reflecting the qualities of all the sensors but not resembling any one sensor.

1.1.2 Sensor Fusion as a Process

In terms of human-computer interaction, current sensor fusion systems provide a cohesive picture, often using graphic and auditory technologies. Display screens, headsets, and auditory warnings are all examples of the final delivery means from which raw sensor data are fused into information and then channeled to the system operator in ways they can comprehend accurately and quickly.

1.1.3 Sensor Fusion Defined

The JDL's (White, 1988) Sub-panel on Data Fusion has defined data fusion as

> …a process dealing with the association, correlation, and combination of data and information from single and multiple sources to achieve refined position and identity estimates, and complete and timely assessments of situations and threats, and their significance. The process is characterized by continuous refinements of its estimates and assessments, and the evaluation of the need for additional sources, or modification of the process itself, to achieve improved results…

This definition provides guidance that describes a closed loop *learning process* that iteratively refines an assessment of a situation, much like a sensor-fused guidance system supplying navigation input to a missile. Note that the JDL definition provides a process statement that uses human information processing techniques of <u>association, correlation, and a combination of data and information</u> from numerous sources (<u>sensor fusion</u>) to identify the goals <u>refine position and identity estimates</u> and to quickly and iteratively make <u>assessments of situations and threats</u> while using a closed loop approach <u>to achieve improved results</u>. What is missing from this definition is the focus ***on how a human can perform this process***, particularly in an environment where automated systems are providing the bulk of the information and the human is under the dynamic conditions of multiple tasking.

A review of the data fusion model as proposed by the JDL describes the data fusion domain as one of parallel processing with sources such as "national, distributed, and local" providing intelligence, electronic warfare, sonar, radar, or other types of information sources as outside the central block that describes the five levels of processing (see figures 1 and 2). In addition, the human-computer interface is seen as outside the central data fusion domain (it is shown to the right side of the diagram). The levels are described in figure 1 and are shown in a model format in figure 2. The JDL model shown in figure 2 also includes another step which is user refinement (an element of a closed loop process). The two figures also show the changes that have occurred in the model over time.

The JDL Model (1987-91)
and the draft revised model (1997)

Level 0 —	**Sub-Object Data Association and Estimation: Pixel/signal level data association and characterization**
Level 1 —	Object Refinement: Observation-to-track association, continuous state estimation (e.g. kinematics) and discrete state estimation (e.g. target type and ID) **and prediction**
Level 2 —	Situation Refinement: **Object clustering and relational analysis,** to include force structure and cross force relations, communications, physical context, etc.
Level 3 —	**Significance Estimation** [Threat Refinement]: Threat intent estimation, event prediction], consequence prediction, susceptibility and vulnerability assessment
Level 4 —	Process Refinement: Adaptive search and processing **(an element of resource management)**

Figure 1. The JDL model, 1987-91 with 1997 revisions (Steinberg, Bowman, & White, 1999).

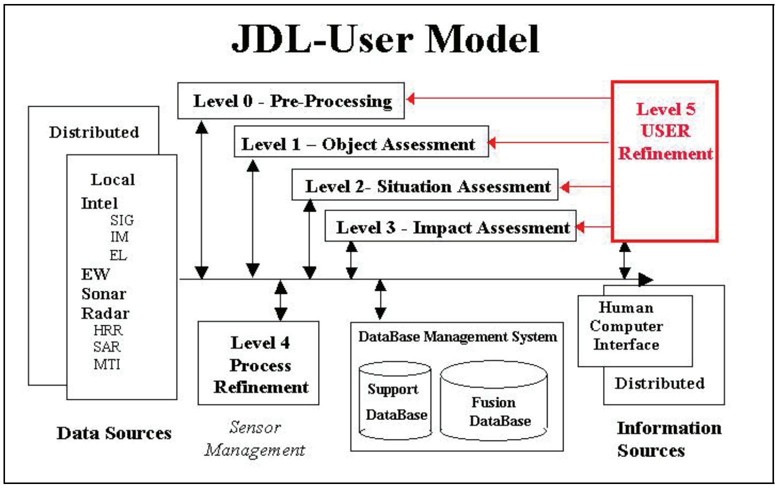

Figure 2. Revised JDL user model, 2003-2006 (Blasch & Plano, 2003).

2. Purpose of Report

The purpose of this report is to provide a general review of the sensor fusion process as defined by the JDL from the perspective of selected human engineering principles.

3. Method

3.1 Human Engineering Principles Applied to Sensor Fusion

The discussion of how humans process information includes a discussion of each of four basic principles that apply to human cognition and subsequent action. These principles are listed next and form the structure for the discussion that follows regarding the specific elements of the JDL model:

Human Versus Machine Process Cycles Comparison

Human Processing of Information

Human Logic in the Processing of Information

Subjective Factors That Affect Human Processing of Cognitive Information, Data Risk, Data Value, and Cognitive Bias

3.1.1 Human Versus Machine Process Cycles Comparison

Although both machines and humans work through an input-throughput-output cycle, the processes within that cycle are very different. Machines, as discussed in this report, represent complex computer-integrated systems that have the ability to collect data from sources or sensors and perform complex activities during complex circumstances, and such machines typically operate in an objective, digital environment where the flow of work is controlled tightly by the processes inherent to that machine's design and programming. For example, a computer uses electricity generated by fuel combustion to create digital data through hardware and software. In contrast, a human metabolizes food to generate electricity to control neurons that process information collected and coded by the senses; this information is subsequently organized by the brain (a cognitive process). Both systems (machine and human) can yield a similar result in many cases, but understanding each of their processes allows a better understanding of the suitability of each of those systems in producing a defined overall system output and is also critical in allocating functions to each. In the case of many examples described in this report, a system usually consists of human and machine contributions toward a complex goal that is ultimately defined by the human.

The human, as opposed to the machine, primarily functions in a subjective world where all information and action are controlled by numerous, subjective processes. This huge difference in basic operating system features provides for the strengths and weaknesses of each system (human versus machine) and the need remains for both to work together in an integrated and complementary fashion to achieve goals that neither could accomplish alone.

The process styles mentioned are biologically or electrically based, but in processing machine data, sensor fusion systems use set filtering methods (e.g., Kalman filters) that "keep updating the system's view of data changes in a very efficient way (i.e., they use the last updated result/data point and only use new information to update it, and then that new data point is later used as the reference point for the next round of new information) overall, which helps reduce the processing requirement on the system. However, it is critical that the algorithms are "human factored" so that they do not get progressively off track" (de Pontbriand, 2006; Kalman, 1960; Kalman & Bucy, 1961).

Other types of information filters include Markov, stochastic, or Bayesian approaches or even neural nets where software agents selectively seek specific information and update their models based on that information (these machines not only selectively use information sources but allow the system to tune itself through an understanding of measurement noise and the use of recursive processes where the system can learn by its mistakes) (Abdi, 2003; Pinheiro & Lima, 1999). However, many of these algorithms are based on fixed sets of logic, whether it is the consideration of Gaussian noise in the collection of data (Kalman filtering) or updating information based on fixed algorithms of a set distribution (other Stochastic methods) (Pinheiro & Lima, 1999).

In the case of humans, the context for these cognitive processes is often based on not only recent or easily available data nor on probabilities but on other factors such as described by Klein as

external knowledge sources unavailable to machine systems. The recognition-primed decision model (RPDM) as postulated by Ross, Klein, Thunholm, Schmitt, and Baxter (2004) was a refinement of a model originally established in 1989 by Klein, Calderwood, and Clinton-Cirocco and describes the theory behind several human cognitive processes. The RPDM postulates that pattern matching, diagnosing a situation, and evaluating a course of action are all higher order processes that humans use in processing information and solving problems. Within that three-element structure, other factors such as perception of a situation as typical or atypical then leads to a recognition involving expectancies: relevant cues, plausible goals, and typical actions. This approach is quite removed from machine logic where a more mechanistic, deductive process is often implemented.

3.1.2 Human Processing of Information

One of the processes illustrated in the JDL diagrams is parallel processing of information at several levels (Steinberg, Bowman, & White, 1999; Hall, 2005). While it is true that humans can process information in parallel, when that task is accomplished, real-time, overall task performance often suffers dramatically (Wickens, 1987). An analogy is the task of driving while one is talking on a cell phone, an action that can and is accomplished with regularity but with significant performance decrements in other tasks. The converse of this dual tasking problem is that people can *either* drive or talk on a cell phone with very good performance but not in parallel unless they wish to reduce their performance of one or both activities dramatically, even though both tasks may be heavily practiced (Cohen, Dunbar, & McClelland, 1990). This area of primary and secondary tasking is also complicated by the human sensory channels being used for that processing (Wickens, 1987). However, it is also possible for humans to process information in parallel with greater facility as that activity becomes more automated via repetition and practice (Wickens, 1987; Cohen, McClelland, & Dunbar, 1990). Humans with a lot of experience in a certain area of activity are called experts, and after an activity is learned to a high level of expertise, it becomes more automated in nature. However, no matter what the level of human of expertise that an individual has in performing a task, that task must compete for limited time and mental resources in order to continue effectively (Sanders & McCormick, 1993). Humans can operate to some degree using parallel processing but not nearly to the degree that automated, mechanical systems can parallel process information. A specific model of how humans process information is discussed in the following sections. The Wickens' model of attention (Wickens & Hollands, 2000) is shown in figure 3.

This model posits that our attentional resources (and by analogy, all our resources) are finite and through various mechanisms associated with human physiology and cognition, address problems through a closed loop process involving sensing data (short-term sensory store), perceiving data (as a sensor would for a machine), and then applying attention resources (energy, motivation, cognition, etc.) through an iterative process to reach an outcome (response). In turn, the closed loop nature of this action is the feedback process called learning. This model of human

performance is similar to that of the JDL process model but has a wide variety of differences that are discussed in this report.

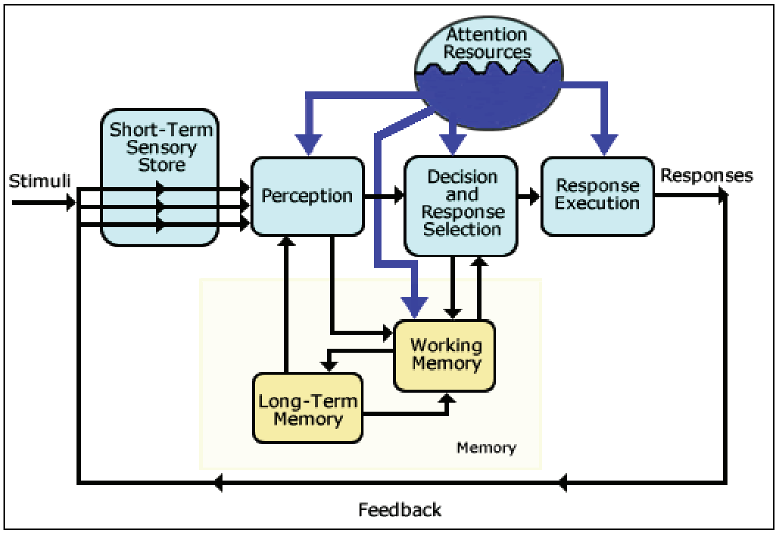

Figure 3. The Wickens' model of human attention (Wickens & Hollands, 2000).

Human cognition or the process of thinking involves actions and outcomes that are currently orders of magnitude more complex than those of any machine. With a computer as an example of a typical machine, it contains an ON and OFF control and then an ever-broadening array of energy flow-switching and storage mechanisms that allow digital processes to occur at the speed of light via a binary, deductive, and digital logic system. However, with all that complexity, even the most powerful computers would be no match for an infant in terms of discovery and cognitive growth. Without the ability of locomotion (inferring continual and dramatically varying sensor input), self-sustainment of operating energy, and a diverse cognition logic basis, a machine cannot progress or learn at the same rate as the human in a variety of domains.

3.1.3 Human Logic in the Processing of Information

How do these human-machine examples relate to the process of sensor fusion in the formation of conclusions and then actions?

If humans processed information purely in parallel, they would have to consider all input at the same time (which they cannot do since they are perceptually limited to only a few channels of information processing [visual, auditory, and proprioceptive]), and those channels are bandwidth limited. If they were processing the same items in series, they would have to consider each item as it contributes to the solution as a sum (a very time-consuming process). Neither approach is regularly used to reach human-derived decisions.

Quite often, humans do not use the deductive logic process where premises follow directly to conclusions such as the method of formal proof that is used in mathematics or that often drives

common machine logic. Instead, humans tend to use a combination of deductive and inductive logic, as well as intuition and emotion to reach general conclusions; however, if formal logic is used, humans often use more of the inductive process (called the method of discovery) or infer from the specific to the general (Searles, 1956).

It is also critical to note that *humans process all information subjectively, even when it is objective in nature*. If posed with the question, "Will the sun rise tomorrow?," virtually everyone would indicate (and truly believe) that the sun will rise tomorrow, but that conclusion is based strictly on subjective information as reinforced by experience. Perhaps one person in a million could fully comprehend celestial mechanics and mathematics to the degree of producing an objective mathematical proof to describe that conclusion, but even that individual would have to rely on "objective data" derived by subjective human experience and intellect. In contrast, machines are strictly objective in terms of basic processes such as the binary effects of current being on or current being off as the basis for action.

The method of deductive logic is more often used in machine processes where conclusions are made from the general to the specific. With a military example of machine logic, the following premises might be made by an automated system: (a) a tank is an object that moves; (b) a moving metal object can be detected by a radar sensor; (c) deductively, an item "tank" can be associated with hypotheses about what constitutes "tank"; (d) a "tank" object can also be tracked or observed by a sensor; (e) a machine can be programmed to confirm that the object is a "tank" if pre-existing, deductive criteria are met (speed, size, heat output, turning radius, etc.). Given this logic stream, that same machine could then transfer a sensor-driven pixel representation of a "tank" object to a screen (in the form of moving pixels). Then that movement of pixels can (with a screen display) be observed by a human who might then conclude that it was "a tank". This same machine system might use elements of the deductive logic stream to assess the "tank" further and provide "conclusions" based on that sensor stream and logic to conclude that the object was a T-73 tank or an M-60 tank.

In comparison, if a human were observing that same "tank" image, s/he might analyze it for familiar patterns (pattern recognition, pattern matching) and then form tentative hypotheses and create a theory about the "object" tank. Carrying this example further, a human might predict an action performed by that tank that cannot currently be accomplished by a machine.

S/he would do so using inductive logic processes, but s/he can also inductively extrapolate the concept and effects of a "tank" to a much greater degree than any machine. For example, a person may see the "tank object" and conclude that an attack could result against a friendly force at a distance of 3 kilometers across a small stream in 20 minutes—a conclusion not backed by deductive logic but that may be correct and was subjectively determined based on experience, stored knowledge, and very dynamic inductive processes. Humans may also mix and match logical methods and in doing so, do not follow a formal logical pathway of pure deduction or induction. For example, if the object is a T-73 tank, it could actually elicit a fear reaction from the

observer because it is likely being driven by an enemy crew with hostile inten-tions—a conclusion that could be programmed into a machine but only resulting in a warning or caution and not as the actual emotion felt by the observer. The element of fear induced by the "tank object" would feed into the information processing by that human observer and could even subjectively influence his or her decision-making process.

The use of a strict deductive process is not possible for a human to accomplish because of the vast number of possible moving objects that *could be* a tank, so humans typically would not deductively identify a moving object as a tank versus a cow versus a cloud versus a tuning fork, but they would use an inductive process to *pattern recognize* and thus quickly determine what that object was based on their past experience (Duda, Hart, & Storck, 2001). This type of reaction to information is also mirrored in the expectancies category of Klein's RPDM (discussed in section 3.1.1).

In contrast to human thinking, machine pattern matching is deterministic and mathematical in nature and is bound by various set algorithms (Haskel, 2007). It typically is not capable of learning and prioritizing in real time to compensate for information loss, ambiguity, or deception. As a tactical illustration of this idea, a tank camouflaged by white sheets and big red balloons could conceivably halt or interfere with the process of automated detection by a machine because that particular camouflage approach simply would not have been chosen by a rational human when trying to deceive another human (based on "common sense") and would be a poor camouflage choice for a human observer. However, a human would quickly recognize that deception because of his or her ability to inductively prioritize and weigh new or unusual information in real time. As humans, we take this process for granted, but machine logic cannot, and thus our abilities as humans currently vastly exceed machines in that regard. Our ability to prioritize and *eliminate information* is as valuable as our ability to collect and process that information.

3.1.4 Subjective Factors That Affect Human Processing of Cognitive Information, Data Risk, Data Value, and Cognitive Bias

The previous paragraphs have mentioned basic logical process differences between humans and machines, but human information processing contains considerably more complexity in how humans process information. A review of some of those processes follows.

3.1.4.1 Data Risk

A human using a machine-fused sensor system is completely dependent on sources of information that are removed from his or her own experience. If all data were created equally, this would not present such a problematic situation, but each bit of data available to a sensor fusion process has an attendant risk level for humans, with some data being quite a bit more risky than other bits of data. When data are collected first hand by the human, data risk can be assessed based on that human's experience, but in the remoteness of a situation where information is far removed from the source, the credibility of those data is usually not included with the presentation of those data. This is all

too common an issue when one is processing printed, verbal, or visual information. Each type of information has various levels of face validity acceptance, as established by the user, and that level of validity drives the acceptance or rejection of the data (Meister, 1985). A pilot tapping a finger on a mechanical altitude display or a computer operator logging out and then back in are examples of how humans test information and assess its risk level. Objectively, a machine has no consequence of risk, i.e., it cannot die from a mistake.

3.1.4.2 Data Value

In terms of information value, simply declaring something to be “the way it is” is low value and high risk, rather than a good logical basis for action. That is, unsupported information is lower value than if that information were presented with the use of some type of objective, externally supported references, citations, or the concurrence of subject matter experts (SMEs).

Humans weigh the value of any data using very complex rules, some of which are not consciously apparent to the human making the decision. Processes of verification of information involve not only logic but circumstance and even an understanding of the motivation someone may have in providing those data (Salvendy, 1987). This may also be thought of in terms of signal detection theory, where the criterion point being set is based on the possible magnitude of con-sequences of a particular type of occurrence. This weighing of data is important for any subjective decision, and one way in which this type of data could be viewed is from the perspective of bias.

3.1.4.3 Cognitive Data Biasing

The term “cognitive bias” implies a conscious or unconscious attempt to weigh an outcome according to some type of pre-existing rule or criterion. Bias may or may not cloud a person’s judgment in regard to making decisions. The issue is that cognitive bias cannot be easily dismissed and can influence human judgments independently of facts.

Cognitive bias is one of the factors that control human actions to some degree, and in this regard, we are very different from a machine that does not operate under that type of subjective condition. Our sensory systems are all susceptible to unconscious and uncontrollable biases, and we call certain of these perceptual biases “illusions”. Most everyone is familiar with optical illusions in which objects do not appear to represent reality, depending on perspective (figure 4). Simply knowing that such biases exist does not make them go away; they are present even in the face of our logical knowledge that tells us what information we think should be presented. As an example, when we view an object such as a set of railroad tracks moving away to the horizon, our visual sense limitations would lead us to believe that the rails converge at a distance, but logically, we know that they do not. As such, we must also recognize that humans are biased not just in the perceptual sense but in the cognitive processes that we employ to collect and process data. The work of Kahneman and Treisman (1984) covers a number of cognitive biases as well as ways that humans process information through rules of thumb, technically known as heuristics. A heuristic

is a pattern of thinking which we apply cognitively, in much the same way as Klein and his RPD model would describe as an expectancy or plausible goal.

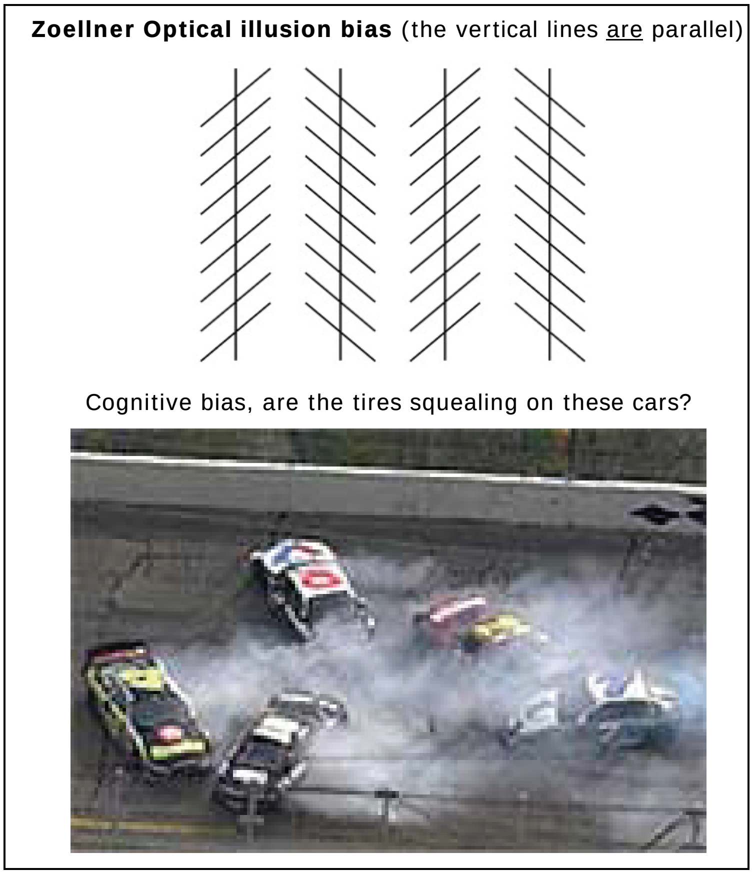

Figure 4. Two types of human bias (illustrations drawn from public domain world-wide web images).

Conversely, a bias can also be a result of learned behavior, which empowers us to make a good decision with a moderate or even low level of information being present. For example, the sound of squealing tires immediately attracts attention because of our prior experience and a bias toward associating that precursor sound with an impending vehicle accident (figure 4). That potential accident may or may not occur, but our previous experience and a bias to trust our experience allows a quick, often life-saving decision to be made in the absence of additional information. Like the startle response to a loud noise, our action is involuntary but is evolutionarily adaptive, and with the RPDM and the previous example, the sound of squealing tires is not only a relevant cue to action but an expectancy of things to come.

The human user of sensor systems data often can conclude outcomes based not on vast amounts of stored information like a computer but on critical, linked memories that indicate an overall trend. This is a critical function of human cognition in that we quite often make judgments based only on fragments of information, and sometimes those judgments are correct.

4. Results

4.1 The Five Levels of the JDL Model of Sensor Fusion

Each of the sensor fusion levels has characteristics, and each of those, in turn, has human factors implications. The following sections discuss the human factors of human interaction with sensor processing. The JDL Fusion Model levels are

- Level 0 – Pre-processing
- Level 1 – Object Refinement
- Level 2 – Situation Refinement
- Level 3 – Threat Refinement
- Level 4 – Process Refinement
- Level 5 – User Refinement

4.1.1 JDL Level 0, Pre-processing: Signal or Feature States

This function is largely out of the realm of human engineering and is one of machine design at the hardware and software level. At this stage, the organization and identification of data are based more on machine capabilities than on human limitations or capabilities. The ability to detect a target within a forest or the range of a sensor is driven more by physics than by human psycho-physics. However, the mechanical features of any sensor or data collection system should consider the capabilities and limitations of human users and should address those inherent values in their design specifications and data products so as not to overload the human who receives that information stream. Sensor systems should output their information in ways to maximize human recognition and processing.

The collection and use of data of any type should consider the ultimate user of those data, and the product of that process should match the abilities of its user. For example, if an electro-optical machine can scan 500 square miles of territory per minute, it must store that information and provide it to an image analyst in a format s/he can understand and comprehend, and most likely, this would not be at the rate that it was originally collected. However, if the purpose of that scan was to identify any large troop movements within that area, as defined by a pre-set moving target identification (MTI) algorithm, then that type of troop movement could be automatically isolated from the less valuable mass of data and transmitted to the analyst in seconds, thereby allowing him or her to make a critical determination of intent without ever having to view all the collected data. In this sense, pre-processing and sensor fusion have refined the data, converted them to useful human information, and communicated that information to an analyst in a form that s/he can

understand and interpret in an order of magnitude less time than if s/he were forced to observe the entire stream of information.

One of the biggest interface mismatches at Level O processing is between what a machine can generate and what a human can absorb. Time, as well as the quantity and quality of information, must be matched so that information is fed to the human at a rate that the human can actually use.

4.1.2 JDL Level 1, Object Refinement: Entity Parametric and Attributive States

This section is the core step of where the JDL model directly interacts with the human information refinement processes. In order to refine, define, or organize objects, human perception is the first step of that process. Human perception steps as described by Foley and Moray (1987) are discussed in terms of the perception of information brought to us by our senses and include information about sight, hearing, rotation, falling and rectilinear movement, taste, smell, touch, vibration, pressure, temperature**,** cutaneous pain, position and movement (kinesthesia). Unfortunately, very few of these sensory faculties are available to help us make decisions in a typical sensor fusion environment, which probably provides only visual imagery and perhaps sound information. For example, an unmanned aircraft system (UAS) operator may only see a video screen image transmitted by his or her UAS, with no aircraft sound, no movement, and no other sensory feedback from that system other than the visual channel. In comparison to actual experience, the information contained in that control environment is very limited and superficial.

In contrast, if that same operator were able to be in that UAS, s/he would see what it sees, hear its operation noise, smell the UAS exhaust, the engine vibration, observe the firing of a missile and its effects, and would thus build an integrated and richer mental model of the concept "UAS". However, in the typical sensor fusion operations environment, nearly all those sources of information about the UAS are not available. The object UAS becomes abstracted when presented by filtering and a single channel presentation (video screen). This principle of abstractness has often led to a disconnection with the object being observed remotely and is seen as a problem with work stations in UAS or other robotic systems (Cooke, Pringle, Pedersen, & Connor, 2006).

All sensor systems, whether they are machine or human, create multiple levels of abstraction since they represent reality but are not <u>the</u> reality (Ceruti, 2004). Most information systems, including sensor fusion systems, would be more effective if they were more immersive in nature and provided complementary sources of information that mirrored reality. In effect, the results would be less abstract and less symbolic. If a UAS operator could actually be on board a UAS, his or her awareness of that system would be enhanced, but that connectedness to the UAS is by definition impossible to achieve. Therefore, the only way to approximate that state is for the operator to have an interface that duplicates the more important system performance features that might be found within and about that UAS. The following object refinement human processes are discussed in relation to level 1 JDL fusion and are believed to be critical to proper human

understanding of a sensor-fused or other mechanical system, as well as being critical to the cognitive processing of any information.

4.1.2.1 The Speed-Accuracy Trade-off

The speed-accuracy trade-off is easily summarized since actions can be fast or accurate but not extreme in both directions at the same time (Sanders & McCormick, 1993). Skilled performance of an expert can be fast and accurate in comparison to that of a novice, but even within that expert, there is always a trade-off between these competing factors in a conflicting and competing resource allocation process (Proctor & VanZandt, 1994).

4.1.2.2 Top-Down Processing

Top-down processing is a series of human cognitive processes that involve the processing and refinement of information (Klapuri, 2007; Parasuraman, 2006). These processes include the Gestalt process, perceptual stereotypes, signal detection, and attention (Wickens, 1987). A discussion of Gestalt processes, stereotypes, and signal detection follows.

4.1.2.3 Gestalt Processes

Gestalt processes refer to the human ability to see patterns in data or imagery that intuitively seem to fit, without detailed analysis or thought (Koffka, 1935). These are a form of pattern recognition that is quick and fairly effortless. In principle, Gestalt perception is often associated with visual processes, but it is not just confined to the visual sense.

Gestalt principles are a very powerful tool to quickly discern patterns in information. For example, in the scene in figure 5, the Gestalt perspective quickly identifies objects that do not “fit” in the picture, so both the unusual conically shaped tree and a concealed tank are visible at a glance because of pattern recognition and matching. The “Gestalt” of this picture is that of two objects that do not “fit” into the background and thus are quickly identified as something other than background.

Figure 5. Gestalt perception (Image from public domain world-wide web).

Stereotypes are learned stimuli that can allow an observer to define objects quicker than if the information associated with those objects were not coded in this manner. This is because they have a certain compatibility, agreed to by a large portion of a population (Bullinger, Kern, Muntzinger, in Salvendy, 1987).

Common stereotypes include color coding (green = good, red = hot, red force = enemy, blue force = allies). This type of perceptual coding system (Proctor & VanZandt, 1994) is used widely within the Army and is typical in the coding of force types (cavalry, artillery, tanks, platoon, battalion, etc.).

Stereotypes often have no inherent information but rely on memorization in order to achieve their meaning; however, a positive trend in symbolic stereotyping is to use objects (icons) that resemble the objects that they portray, so for example, a tank icon would be displayed with a track, a basic tank chassis outline, and a gun barrel, each bit of information contributing to the concept “tank,” and to a limit, this provides faster and more accurate detection and discrimination by the observer.

Stereotypes also have limitations in the amount of information they can convey and they primarily focus on quick, not necessarily accurate, discriminations. As figure 6 shows, many military symbols do not have realistic (iconic) qualities; thus, they must be memorized for content. However, some of the symbols do have iconic qualities (e.g., helicopter blades or the outline of a tank [armor]).

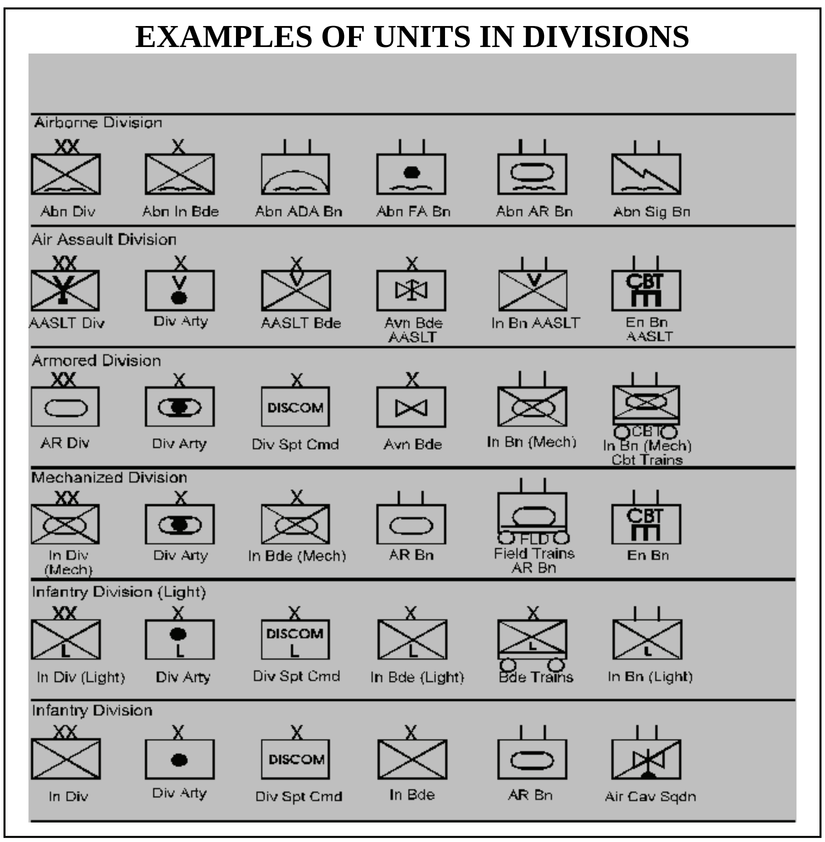

Figure 6. Stereotypes and iconic symbols (image from the Federation of American Scientists, 2006).

4.1.2.4 Signal Detection Theory

The term “signal detection theory” was first used in electronic signal communication in the 1950s and subsequently was adopted and expanded greatly by psychologists to describe the perception of a signal in the presence of noise (Shannon, 1948). For psychologists, the term “signal” has been broadened to tasking, goals, or perception, while the term “noise” indicates any factor, environmental or other, that interferes with that process.

This concept of signal detection is typically diagrammed with the use of two normal curves. One curve represents the signal (goal, task, perceived object) and the other curve represents noise or anything that interferes with that process of perception; the intersection of the two curves represents the signal-to-noise relationship for a circumstance. If the curves are widely separated (lower part of figure 7), there is little interference with the task or goal, but as the noise curve further intrudes on the task or goal, the greater the level of masking and thus, the greater difficulty of performing the task or meeting the goal (illustrated by the upper part of figure 7). When the two curves overlap completely, the goal or task is not possible. This concept is a powerful analog for human performance in terms of human workload.

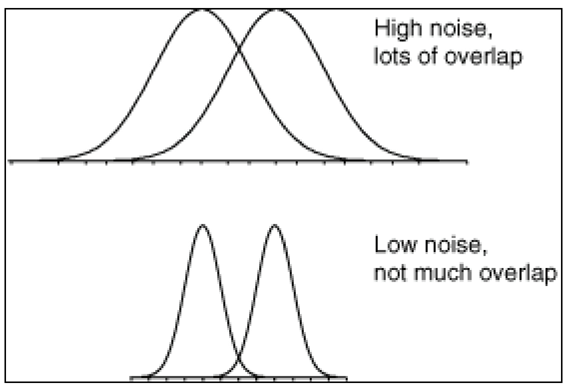

Figure 7. Signal detection example (Heeger, 2007).

4.1.2.5 Attention and Vigilance

Humans, unlike machines, do not operate on a set or binary type of scale (that is, on or off). As a system, they operate through a variety of operating continua, one of which is called attention. For any task, a person’s involvement with that task is driven by his or her level of attention. Generally, poor attention equals poor performance, proper attention equals proper performance, and over-attention can lead to a cognitive myopia or attentional tunneling (excessive focus on too small an area).

The presentation of any data involves time, and one area that humans are not noted for is their ability to sustain vigilance for extended periods of time. For example, during World War II, sonar operators were shown by Mackworth to have greatly diminished vigilance after only 30 minutes of operation, often missing vital signals because of boredom and a vigilance decrement (Parasuraman, 2007). UAS operators often are confronted by long periods of inactivity followed by frantic action,

followed again by inactivity, and this work environment is not conducive to maintaining vigilance. Performance decrements have been modeled and reductions in effectiveness predicted (Cooke et al., 2006), and there is a large body of research that concerns the loss of performance with sustained vigilance. A sample of research showing a short-term vigilance decrement is shown in figure 8 and is called the Mackworth (1948) vigilance curve. This curve involved the results of detecting changes in the ticking of a clock over time. Essentially, it showed that for boring, repetitious, or infrequent tasks, performance suffers greatly.

Contrary to vigilance decrement, sensor fusion system users must be presented with information for a time adequately long enough to process that information (minimal response time limits). Continuity of information flow at the right pace is critical in matching machine feeds of information and tasking to the abilities of the user.

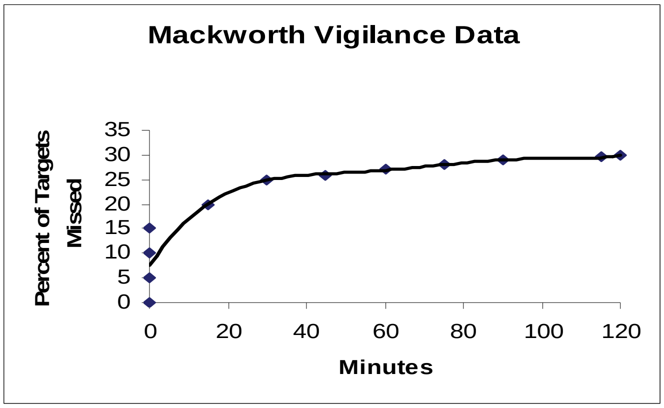

Figure 8. Mackworth (1948) vigilance curve (human performance decrement over time).

4.1.3 JDL Level 2, Situation Refinement

After the perceptual elements have been addressed by the analyst at Level 1 processing, situation refinement begins to become more dominant at the JDL Level 2 (situation refinement level). At this stage, the human processes of cognition (rather than just perception) become more involved. It is also important to note that there is no clear defining line between human perception and cognition, and perceptual biases can easily cross over into cognitive processes and conclusions.

Raw data from external sources are pre-processed by mechanical systems in Level 0, perceptually arranged and manipulated in Level 1, and are then evaluated in Level 2. As an example from a military intelligence analyst environment, the six functions associated with this level are (Blasch & Plano, 2003)

1. **Aggregation** of information into entities or force structures,
2. **Determination** of relationships and working rules,
3. **Interpretation** of the actions of entities of forces,

4. **Determination** of the overall purpose of large and small actions,
5. **Hypotheses** of current and future activities and testing those hypotheses,
6. **Resolution** of anomalous factors and the consideration of deception.

Each of the six processes within Level 2 builds an awareness of a situation and does so iteratively as information is brought together, tested, and evaluated. There is never actually an end product for situation awareness (SA); it is an ongoing, dynamic process that continues even after the resolution of a particular situation.

Before discussing the six individual processes of Level 2, it would make sense to define SA since it is an awareness of information in the first place that then proceeds to all further processes. Dr. Mica Endsley's (1988) definition of SA is the commonly accepted origin of that term:

> The perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future.

The user of a sensor fusion system must perceive information that is dependent on that system's perceptual abilities and limitations. S/he must be able to comprehend that information (thus, much of the discussion here about the processes of comprehension and cognition), and then s/he must be able to project or predict a possible outcome, based on that perception and comprehension. Both SA and sensor fusion systems have a similar closed loop process and use an input-throughput-output cycle that is familiar to industrial engineers and human factors practitioners. Considering this overall perspective of SA, the following steps of the JDL level 2 model are discussed in terms of human factors principles.

4.1.3.1 JDL Level 2, Step 1: Aggregation of Human-Related Data

Of the six processes, the process of aggregation is readily suitable for integration with current automated systems. The ability to collect data and determine correlations or separate data into categories is most easily done by automated means as directed by the human. For example, given a large collection of enemy combatants and the goal of finding a key person(s) from that database, a database sorting program can immediately sort those players into categories as defined by a military intelligence analyst. Factors associated with geography, age, birth place, combatant service affiliation, notable activities that the person has been involved with, places where s/he has lived, personnel s/he has been in contact with, education or schooling affiliations, friends, family lineage, military specialty, and a wide variety of known variables can all be sorted and organized by an automated routine. Aggregation could also apply to combination of sensor data from a variety of sources, the prioritization of those data, and the use of those data to build a model or reach a conclusion.

4.1.3.2 JDL Level 2, Step 2: Determination: Human Relationships and Attributes

Determination of relationships, attributes, and working rules is an area where automation could provide help to the human in the loop. With the military intelligence domain as an example,

enemy personnel relationships can be provided by the correlation of information (such as which enemy personnel might be related to whom), which set of personnel might be associated with another set of personnel in a chain of command, or a general understanding of the psychological or sociological working rules for determining such enemy activities. Nevertheless, machine-based associative algorithms for enemy personnel matching could provide clues to human analysts of correlations not obvious from the mere collection of human intelligence (HUMINT) in the field.

4.1.3.3 JDL Level 2, Step 3: Interpretation

This sub-process seeks to answer the question why was an action taken, and it often involves human subjective data. It seeks to answer questions such as “What role did this action have?” or “What effect would an action like this have on some defined process?” It is attempting to derive meaning from actions. It is almost entirely a cognitive process that is aided little by current automated systems. One way in which an automated system might be able to contribute to answering these types of questions could be in the graphic presentation of magnitude of effects or associations with the use of pie charts or graphs that show trends. By compiling numeric data and reporting them in a graphic way, an analyst can improve his or her overall understanding.

4.1.3.4 JDL Level 2, Step 4: Determination: Large and Small Actions and Their Effects

This process is like construction of a jigsaw puzzle with the analyst placing piece after piece of the puzzle together to assess its impact on the overall picture. Not all information is created equally; some provides higher information content than others. Human beings have a fairly good ability to generalize from small pieces of information and to determine a sense of proportion of the value of information. This intuition process is based on past knowledge and often can manifest itself in conclusions with only a small amount of information being required; however, it can also lead to quick conclusions not supported by facts.

4.1.3.5 JDL Level 2, Step 5: Hypotheses: Testing of Human-Related Information

The formation of hypotheses by the sensor fusion information user is perhaps one of the most important cognitive tasks that s/he must perform, and that testing is often performed with subjective data. Often, a checklist or matrix approach can be used by the analyst to evaluate (but not prove) a hypothesis. In many cases, intuition alone is the basis for decision, whereas some more formal and structured method of testing hypotheses should be encouraged.

4.1.3.6 JDL Level 2, Step 6: Resolution: Situational Human Factors

This process often involves unusual cases where ambiguity is very high. If a situation does not appear to make sense or fit an established pattern, it very well may be some act of deception accomplished deliberately to raise doubt, promote confusion, or preempt the use of resources in its investigation. This aspect of sensor fusion has no machine analog since machines have not yet been created to lie, subjectively obscure, or in other ways purposefully distort information. The creation of decoys, setting up false troop movements, creation of meaningless activity, propaganda releases, hacking, and other forms of deception are often challenges to military sensor fusion

systems users because they impugn, distort, or destroy the quality of information that the sensor fusion system is transmitting.

4.1.4 Level 3, Fusion: Threat Refinement, Estimation, Prediction, and Utility

This stage of the sensor fusion process begins to isolate causes, to predict outcomes, and to assess the utility of those actions. At this stage of sensor fusion, the human and the machine are taxed with interpolating data, creating predictive outcomes, and then determining if those predictions have utility in comparison to the real-world events they are modeling. The third step of SA, "prediction," is critical in this stage.

4.1.5 Level 4, Fusion: Process Refinement and Human Learning

Reviewing the sensor fusion process from start to finish is also a learning process and involves training. Since training is also a cognitive process, psychologists or human factors experts should be consulted when a training plan or system is being created. Improvement and optimization of any process is the domain of industrial engineering, but the psychological elements of learning are taught as basics to human factors practitioners. The learning process should always be closed loop, that is, iterative and repetitive in order to continually improve a product or a process.

4.1.6 Level 5, Fusion: User Refinement

This process should involve far more than visualization, but it is currently associated with visualizing enhancements of the other four levels**.** This stage also reflects the ability of the user to customize or tailor the process used to achieve the sensor fusion system goals. It must be remembered that human beings have five sensory channels, each of which provides information to support cognitive activities. If a system interface is limited only to visual processes, it is inherently disconnected with how humans naturally process information. It is understandable that much of our information is acquired visually as we sit in front of a computer screen and observe data products; however, our ability to learn in the real world is greatly enhanced by our using the rest of our sensory channels to process information. The following elements could be added to tools for user enhancement beyond the most common visual channel and primarily reflect future technological or human engineering approaches to fusing data from complex sources such as HUMINT.

4.1.6.1 Auditory Feedback and Learning Human-Machine Comparisons

The human auditory channel is a rich, high-density communication medium. In the analysis of speech alone, many linguistic principles can be used in providing feedback and learning through sensor fusion. However, linguistics alone is a very complex study and not currently very successful in terms of machine processing, other than simple word-for-word or phrase translator systems. In contrast, human observers using logic and experience can extract meaning from text or spoken language which is veiled by semantic features such as sarcasm or formalism that contain a very great amount of information but would not be detected by machine translation systems. Psycholo-

gists understand that inflection, the choice of words, and the manner in which they are delivered all contain huge amounts of information that are lost when those words are merely written. In this respect, human perception of auditory feedback, when understood in the context of linguistic and semantic rules, can provide a human with far better information conclusions than a machine can.

4.1.6.2 Sociological and Biodynamic Factors

As humans who live in a sociological setting, posture, gesture, physical movement, and internal bio-physiological factors can tell us a lot about human behavior. Body language is a colloquial term for an externally driven, sociologically influenced communication process. It is entirely possible that a sensor-fused system could even provide cues from posturing, gestures, or movements that could indicate critical details such as deception and denial. In terms of human perception and cognition, simply observing an enemy's spoken language over time may contribute to a sociological perspective that helps an analyst better in fusing complex information. In the past, lie detectors were used to assess, from a physiological perspective, the presence of deceptive techniques with the use of only one type of electro-physiological measurement (electromyography). In the future, powerful, automated routines could be developed to assess deception and denial by combinations of bio-analytical routines involving eye movement, posture, limb movement, or physiological measures such as electro-cardiogram, electro-encephalography, or electromyography.

5. Summary Discussion

This report has briefly covered the essential elements of the JDL definition of sensor fusion and discussed how, for each of those elements, human factors can contribute valuable human-centered information to those processes and products of sensor fusion. The information conveyed in this report was presented to demonstrate that human engineering principles, the principles of human psychology, cognition, learning, and an understanding of human behavior can all help create a better method of fusing data into useful information.

6. Future Directions

The tasking demands required for many military operations are bound to become more, rather than less, complex over time. Asymmetric, small-scale war operations in a network-centric environment provide personnel with the risk of being lost in a sea of data, while having to anticipate an enemy's action that is not traceable by simple observation of battalions of tanks or thousands of troops *en masse*. In addition, being removed from direct, experiential contact with the enemy and

the ability to employ all of one's senses in assessing information can result in superficial judgments based on information that is brittle in context, rather than rich in content. In addition, the current warfare environment still has huge risks associated from enemy combatants that do not follow many of the historic rules of warfare, nor do they provide traditional trails of information. In order to combat this trend, technology and sensor-fused systems have been implemented to compensate for this change in direction.

Planning for conventional military operations against conventional military forces may not be the common battle environment for this generation, but that process must adapt to this new environment in order to maintain the upper hand in maintaining capable military strength. The use of sensor-fused systems has only now begun to emerge from a beginning in rudimentary tracking algorithms to the concept that sensor fusion may provide a very powerful tool in synthesizing and simplifying information. This fusion process may have more inherent value than matching large numbers of conventional military forces against each other in a well-defined tactical environment. If knowledge is power, sensor fusion may be a powerful tool in future military operations.

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Acronyms

F-22	Fighter, Model 22, U.S. Air Force
HFE	human factors engineering
HUMINT	human intelligence
JDL	Joint Directors of Laboratories
MTI	moving target indication
RPDM	recognition-primed decision model
SA	situation awareness
SME	subject matter expert
SRI	not an acronym
UAS	unmanned aircraft system (formerly called an unmanned aerial vehicle [UAV])

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